A Robust Face Recognition System Based on Curvelet and Fractal Dimension Transforms

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***Abstract*— In this paper, a powerful face recognition system for authentication and identification tasks is presented and a new facial feature extraction approach is proposed. A novel feature extraction method based on combining the characteristics of the Curvelet transform and Fractal dimension transform is proposed. The proposed system consists of four stages. Firstly, a simple preprocessing algorithm based on a sigmoid function is applied to standardize the intensity dynamic range in the input image. Secondly, a face detection stage based on the Viola-Jones algorithm is used for detecting the face region in the input image. After that, the feature extraction stage using a combination of the Digital Curvelet via wrapping transform and a Fractal Dimension transform is implemented. Finally, the K-Nearest Neighbor (K-NN) and Correlation Coefficient (CC) Classifiers are used in the recognition task. Lastly, the performance of the proposed approach has been tested by carrying out a number of experiments on three well-known datasets with high diversity in the facial expressions: SDUMLA-HMT, Faces96 and UMIST datasets. All the experiments conducted indicate the robustness and the effectiveness of the proposed approach for both authentication and identification tasks compared to other established approaches.**

Keywords*— *Face Recognition, Curvelet Transform, Fractal Dimension, Fractional Brownian Motion, SDUMLA-HMT database, Faces96 database, UMIST database.

I. INTRODUCTION

In the last few decades, increasing the use of many developed and sophisticated techniques of hacking and forgery led to increased demand for alternative methods to authenticate a person's identity [1]. Many different kinds of the biometric-based pattern recognition systems were widely used. These biometrics traits can be divided into two types, physiological characteristics such as Face, Iris, Fingerprint, Hand Veins and etc., or behavioral characteristics such as Signature, Speech, Gait, Voice, and Keystroke recognition [2]. Personal authentication based on the biometric features has many advantages over the traditional methods like the passwords, ID cards and PIN, because it is difficult to be transferred, lost, forgotten or duplicated. In addition, employing the biometrics in the task of authenticating a person's identity are more convenient and user friendly than the traditional methods, so that the clients do not need anything to remember or to carry with them [3]. Finally, the security level achieved using the biometric systems is higher than that using traditional methods. Face recognition is one of the most popular biometric systems that have received a significant attention in the research community due to its accuracy and low cost. Face recognition has appeared to offer a number of characteristics over other biometric systems. Face recognition systems have the added advantage that the user can be identified without knowing he is being monitored. In addition, the biometric systems that depend on using the same sensor device to acquire the biometric trait from multiple users (e.g. Fingerprint recognition) can cause some health risks by transferring germs and/or some infectious diseases from one user to the other [4]. Moreover, face recognition has a wide range of applications in many areas such as access control systems, check points, ATM machines, security and surveillance systems, and others daily human applications [5]. However, developing and designing a face recognition system is one of the most challenging problems in the image processing, computer vision and pattern recognition fields. Therefore, many factors and problems must be taken into account when developing any biometric system based on the face image, due to the variations and changes in the face image, such as illumination and facial expression changes, multi-views, and other occlusions from wearing glasses and hats and the presence of beards and mustaches, etc. [4][6].

Generally, a number of approaches have been proposed and refined to overcome all these drawbacks and problems but very few of them are capable of working under fully unconstrained conditions. These approaches can be divided into three categories: Feature-Based, Holistic and Hybrid approaches [7]. In this paper, a new feature extraction method based on combining the characteristics of the Curvelet transform and Fractal dimension technique is proposed. The proposed system consists of four stages. Firstly, a simple preprocessing algorithm based on a sigmoid function is applied to standardize the intensity dynamic range in the input image. Secondly, a face detection stage based on the Viola-Jones algorithm is used for detecting the face region in the input image. After that, the feature extraction stage using a combination of the Digital Curvelet via wrapping transform and a Fractal Dimension transform is implemented. Finally, the K-Nearest Neighbor (K-NN) and Correlation Coefficient (CC) Classifiers are used in the recognition task. In this paper, we will concentrate on the

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proposed feature extraction approach by explaining the motivations behind using it and analyzing its strength. This paper is organized as follows: some related works will be discussed in Section II. Section III describes the proposed face recognition system. The experimental results are presented in Section V. Finally, conclusions and future research directions stated in the last section.

II. Related Works

In the last years, face recognition has received considerably more attention in the research community than other biometric features due to its accuracy, low cost and ease of capturing face image without the user's cooperation. Generally, a number of algorithms were proposed and developed as an attempt to overcome some or all the problems in face recognition. However, very few of these techniques are capable of working under fully unconstrained conditions. For instance, a number of hybrid features extraction methods have been proposed by Tzung J., [8]. These methods are mainly based on the Wavelet transform, Linear Discriminant Analysis (LDA), and the Nearest Feature Plane (NFP) and Nearest Feature Space (NFS). The performance of the proposed approaches was evaluated on two databases: IIS face database and ORL database. In [9] J. Ye and G. Tan have proposed a face recognition system based on the Gabor filter respons, Digital Curvelet transform followed by 2D Principal Component Analysis (PCA), the performance of the proposed system has been assessed on the ORL database and the best obtained results was 95.5%. In addition, an efficient face authentication system was proposed by L. Fang and et al. [10] by decomposing the face image using Wavelet transform to extract the low frequencies followed by 2D Principal Components Analysis and Fisher linear substitution to extract the components vector. Finally, the Support Vector Machine (SVM) was adopted for the authentication purpose. In [11] Huilin X. and et al presented a new facial feature extraction algorithm named as 2D-Fisher Linear Discriminant (2D-FLD). In this work, the performance of the proposed approach was assessed on the ORL and UMIST face databases and the conducted experiments proved its efficiency compared to other methods such as PCA and the combination between the PCA and the FLD. In [12] a new dimensionality reduction technique for face recognition system named as Diagonal Locality Preserving Projections (DiaLPP) was proposed. This technique depends on finding the optimal projection vectors by using the information in both the rows and columns of the face images. The performance of the proposed technique was compared with other existing methods such as Locality Preserving Projection (LPP) and 2D-Locality Preserving Projection (2DLPP). In [13] Asha R. Arnold and et al presented a face recognition system based on a hybrid approach for capturing the shape and texture information of the face image. This technique depends on the gradient orientation histogram to extract the shape features, and the Local Binary Pattern (LBP) to capture the texture information. Finally, a combination of the hash table and binary tree is adopted for the classification task.

III. The Proposed METHODOLOGY

As shown in Fig.1, the proposed system starts with simple preprocessing algorithm using sigmoid function to reduce the illumination changes effect by expanding and compressing the values of the dark and bright pixels in the face image, respectively. This is followed by detecting the face region in the face image using the Viola-Jones detector [14]. Viola-Jones detector works on building a cascade of weak classifiers using the AdaBoost learning algorithm to extract and detect the most important facial features in the face image, such as nose, eyes, and mouth, then use the to detect the face region in the input image. More details about this detector can be found in [14]. In the feature extraction stage, an efficient and robust feature extraction approach is proposed based on integrating the advantages of the Curvelet transform with the Fractal dimension transform. Although, number of studies have demonstrated that the Curvelet transform can serve as a good feature extraction or a dimension reduction tool for pattern recognition problems like fingerprint recognition and face recognition due to its ability to represent crucial edges and curves features more efficient than other transformation methods.

However, the Curvelet transform cannot overcome the effects of large changes in illumination conditions, shadows, multiple views of face images and occlusions from wearing glasses or hats. As a result, the Curvelet transform will not be able to describe the face texture roughness and fluctuations in the surface efficiently, which have a significant effect on the recognition rate. All these factors together were behind the adoption of the fractal dimension transform here to provide a better description of the face texture under different environmental conditions. The fractal dimension has some important properties such as a self-similarity, which means that an object has a similar representation to the original under different magnifications. This property can be used in reflecting the roughness and fluctuation of image's surface where increasing the scale of magnification provides more and more details of the imaged surface. In addition, the non-integer value of the fractal dimension give a quantitative measure of the objects that have complex geometry and cannot be described by an integral dimension (an example is the length of a coastline) [15],[16]. Many methods have been proposed to calculate fractal dimension, such as Box-counting, Differential Box-counting and Fractal Brownian Motion (FBM), and other methods can be found here [17]. However, fractal estimation methods are very time consuming and cannot meet real-time requirements. Hence, to address all the above limitations and drawbacks, a novel face recognition algorithm based on merging the advantages of a new multidirectional and anisotropy transform, specifically the Curvelet transform, with fractal dimension is proposed. In this paper, the fractal dimension is estimated using Fractional Brownian Motion (FBM) and the proposed method named as a Curvelet Transform-Fractional Brownian Motion (CT-FBM).

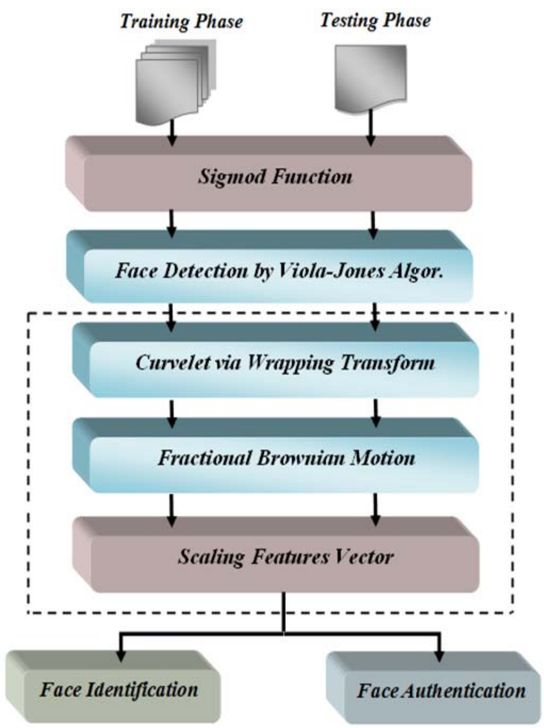

Fig.1. The block diagram of the proposed face recognition system.

A. Curvelet Transform

The Curvelet transform was first introduced by Candes and Donoho in 1999 to overcome the drawbacks and limitations of widely used multiresolution methods such as the Wavelet transform and Ridgelet transform. The multiscale transform principle is a property common to Curvelet and Wavelet transforms where each has multiple frames indexed by location and scale parameters. However, the Curvelet transform unlike the Wavelet transform, has a very high degree of directional flexibility and the frame size is subject to the anisotropic scaling principle [18]. These characteristics of the Curvelet transform can lead to a good and a strong representation of the edges and curves which are considered to be the most important facial features. In this paper, the wrapping based Curvelet transform described below is adopted, due to its advantages over other Curvelet implementations such as Ridgelet and (USFFT) based forms of Curvelet transform. In addition to its abilities to reduce the dimensionality of the data and capture the most crucial information in face images such as edges and curves, play a significant role in increasing the recognition power of the proposed system. Firstly, the Curvelet via wrapping transform function is defined as:

$$\boldsymbol{c(j,l,k) := \langle f, \varphi_{j,l,k} \rangle} \qquad (1)$$

Where $\langle\ \rangle$ refer to the inner product between the Curvelet function $\boldsymbol{\varphi_{j,l,k}}$ and the Cartesian form of the input image $\boldsymbol{f}$, and $\boldsymbol{j}$, $\boldsymbol{l}$ and $\boldsymbol{k}$ refer to the variables of scale, orientation, and position, respectively [18]. Secondly, the Curvelet via wrapping can be implemented by taking the input image as a Cartesian array $\boldsymbol{f[n_1, n_2]}$ such that $0 \leq n_1 < N_1$, $0 \leq n_2 < N_2$, where N_1 and N_2 are the dimensions of the original image. Then a number of Curvelet coefficients are generated and indexed by a scale $\boldsymbol{j}$, an orientation $\boldsymbol{l}$ and two spatial location parameters $\boldsymbol{k = (k_1,k_2)}$ as output. The major steps implemented on a facial image to obtain the Curvelet coefficients can be summarized as follows:

- Apply the 2D-Fast Fourier Transform (2D-FFT) on the input image $\boldsymbol{f[n_1, n_2]}$ to obtain $\boldsymbol{\hat{f}[n_1, n_2]}$, $-\boldsymbol{n/2} \leq \boldsymbol{n_1, n_2} < n/2$.

- The transformed image is divided into a collection of Digital Corona Tiles (Wedges) and each wedge can be reached by specifying the scale and angle parameters. For each scale $\boldsymbol{j}$ and angle $\boldsymbol{l}$ the product between $\boldsymbol{\hat{f}[n_1, n_2]\, \tilde{U}_{j,l}[n_1, n_2]}$ is implemented, where $\boldsymbol{\tilde{U}_{j,l}}$ is the discrete localizing function defined by a pair of radial window $\boldsymbol{W(r)}$ and angular window $\boldsymbol{V(t)}$. These windows are calculated as follows:

$$\sum_{j=-\infty}^{\infty} \boldsymbol{W^2(2^j r) = 1} \qquad \boldsymbol{r} \in (\frac{\boldsymbol{3}}{\boldsymbol{4}}, \frac{\boldsymbol{3}}{\boldsymbol{2}}) \qquad (\boldsymbol{2})$$

$$\sum_{l=-\infty}^{\infty} \boldsymbol{V^2(t-1) = 1} \qquad \boldsymbol{t} \in (\frac{\boldsymbol{-1}}{\boldsymbol{2}}, \frac{\boldsymbol{1}}{\boldsymbol{2}}) \qquad (\boldsymbol{3})$$

- The wrapping procedure is applied to wrap this product around the origin and obtain $\boldsymbol{\tilde{f}_{j,l}[n_1, n_2] = W(\tilde{U}_{j,l}\hat{f})[n_1, n_2]}$ where the range for $\boldsymbol{n_1}$ and $\boldsymbol{n_2}$ is now $0 \leq \boldsymbol{n_1} < L_{1,j}$ and $0 \leq \boldsymbol{n_2} < L_{2,j}$. $L_{1,j} \sim 2\ j$ and $L_{2,j} \sim 2\ j/2$ are constants.

- The inverse 2D FFT is applied for each $\boldsymbol{\tilde{f}_{j,l}}$, and then the Curvelet array is added to the collection of Curvelet coefficients. See Fig.2. (a) and (b).

B. Fractal Brownian Motion

To the best of our knowledge, this is the first attempt to use Fractal Brownian Motion (FBM) as a facial feature extraction method. The FBM is a non-stationary model and is often used in medical imaging [16],[19] due to its power to enhance the original image and make the statistical features more distinguishable.

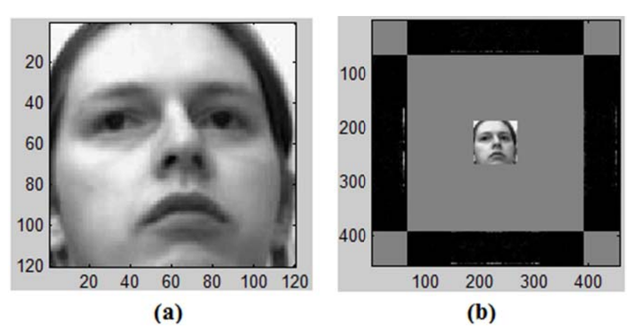

Fig.2. (a) The original face image and (b) its Curvelet coefficients.

According to Mandelbrot [15], the FBM is statistically self-affine, which means that the fractal dimension value of the FBM is not affected by linear transformations and scalings. Therefore, the (FBM) is invariant under any normally observed transformations of the face images. For any (***N***×***N***) size image region, the FBM can be defined as the mean absolute difference of pixel pairs on a surface at different scale ranges, which can be represented as:

$$\boldsymbol{E(\Delta I) = k\Delta r^{H}} \qquad (4)$$

Where$\boldsymbol{E}(\ )$ is an expectation operator and$\Delta \boldsymbol{I} = |\boldsymbol{I}\,(\boldsymbol{x_2}, \boldsymbol{y_2}) - \boldsymbol{I}\,(\boldsymbol{x_1}, \boldsymbol{y_1})|$ is the absolute intensity difference between pairs of pixels separated by distance$\Delta \boldsymbol{r} = [\,(\boldsymbol{x_2}, \boldsymbol{x_1})^2 + (\boldsymbol{y_2}, \boldsymbol{y_2})^2]^{1/2}$. $\boldsymbol{K}$ is a scaling constant $> \mathbf{0}$ and $\boldsymbol{H}$ is called the Hurst coefficient. Due to a discrete form of an image, the $\Delta \boldsymbol{r}$ value between the all pixels is usually an integer value $\boldsymbol{d}$ from ***1*** to ***N-1***. Thus (4) can be expressed as follows:

$$\frac{\mathbf{1}}{\boldsymbol{N_d}} \sum_{\Delta r = d} \Delta \boldsymbol{I}_{\Delta r} = \boldsymbol{k d^{H}} \qquad (5)$$

Where $\boldsymbol{N_d}$ is the total number of pixel pairs with a distance of $\Delta \boldsymbol{r} = \boldsymbol{d}$. By taking the log function for both sides of (5), we deduce the following form:

$$\boldsymbol{log}\left(\frac{\mathbf{1}}{\boldsymbol{N_d}} \sum_{\Delta r = d} \Delta \boldsymbol{I}_{\Delta r}\right) = \boldsymbol{H}.\boldsymbol{log}(\boldsymbol{d}) + \boldsymbol{log}(\boldsymbol{k}) \qquad (6)$$

Now, a log-log graph is taking of both sides of (6), after $\Delta \boldsymbol{r_{min}}$ and $\Delta \boldsymbol{r_{max}}$ are determined and least squares linear regression is used to estimate the value of the slope, which represents the value of $\boldsymbol{H}$. Finally, the fractal dimension of the image surface is estimated as follows:

$$FD = 3 - H \qquad (7)$$

In this paper, the face image of size (***M***×***N***) is transformed to its Fractal dimension form by applying a kernel function ***fd(p,q)*** of size (***n***×***n***) on the entire face image, as explained in Fig.3. The kernel function operates by block processing on (*7×7*) neighboring pixels of the face image and calculating the fractal dimension value of each pixel as explained above. As a result the fractal transformed face image is obtained. The size of the kernel function was determined empirically, noting that increasing its size can affect the accuracy of the calculated Fractal dimension and the obtained image becomes less distinct, while decreasing its size can result in insufficient number of the surrounding pixels to accurately calculate the Fractal dimension value. The kernel function is computed and applied to the face image as defined in (8) and (9). This implementation of the FBM has the ability to enhance the edge representation and create an illumination invariant representation of the face image without increasing the noise level.

$$\boldsymbol{fd(p,q) = 3 - \left(\log\left(\frac{\Delta I}{k}\right) \Big/ \log(\Delta r) \right)} \qquad (8)$$

$$\boldsymbol{FDImage\,(x,y) = \sum_{p=-a}^{a} \sum_{q=-b}^{b} fd(p,q) I(x+p, y+q)} \qquad (9)$$

Where, $\boldsymbol{a}$ and $\boldsymbol{b}$ are nonnegative integer variables, which are used to center the kernel function on each pixel in the face image and are defined as: $\boldsymbol{a}$ and $\boldsymbol{b} = \boldsymbol{ceil\ ((n-1)\ /2)}$. Fig.4 shows the approximation of the Curvelet transform and its fractal transformed image. After, the fractal transformed image has been obtained it is reshaped into a feature vector of one dimension. The size of the output feature vector for the SDUMLA-HMT, Faces96 and UMIST databases is 2809, 2401 and 1681, respectively.

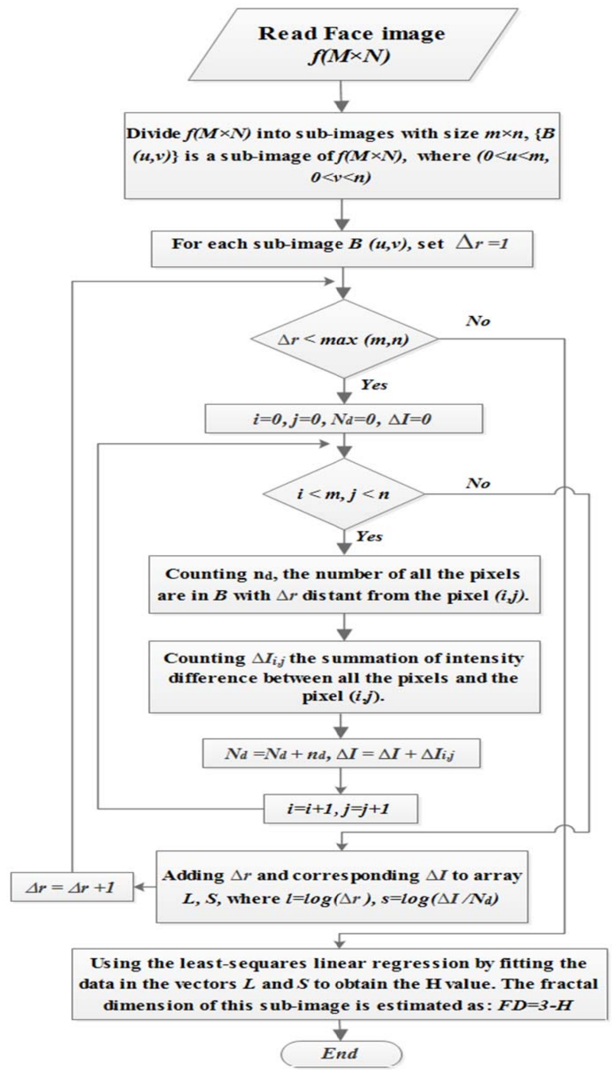

Fig.3. The block diagram of the implementation of the FBM.

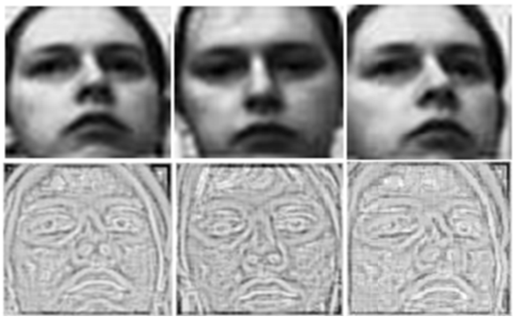

Fig.4. The top (row) is Curvelet output image and the bottom (row) its fractal transformed image.

IV. Experimental Results

In order to investigate and demonstrate the effectiveness and robustness of the proposed approach a number of experiments were conducted on three databases consisting of a wide range of facial images with high diversity in facial expressions, poses, lighting conditions and accessories. The first database is the SDUMLA-HMT face database. This database consists of 106 subjects and each one has 84 face images which have been taken from 7 viewing angles and under different experimental conditions such as, facial expressions, accessories, poses, and illuminations. The main purpose of this database is to simulate the real world conditions during face image acquisition. The image size is (640×480) pixels and Fig.5 shows an example from the SDUMLA-HMT face database. To the best of our knowledge, this is the first work that uses all the users in this database for both authentication and identification tasks. The second database is the Faces96 database, which contains a total 3040 images of 152 individuals, both male and female and each individual has 20 frontal images with a complex background, large head scale variation and face position translation. The size of every image is (196×196) pixels. Fig.6 shows some examples from the Faces96 database. The UMIST database is the third one, which contains a total 564 images of 20 individuals with mixed race, gender, and different appearance. As shown in Fig.7 each individual has a set of images covering large pose variations, from profile to frontal views with a size of (220×220) pixels and 256-bit grayscale. In this database, the number of images per person is not fixed; it changes from 24 to 36. In order to ensure that each one has the same number of images in all experiments 24 images from each individual were selected. In this work, a number of experiments were conducted to evaluate the performance of the proposed system in both authentication and identification tasks and comparison was carried out with existing approaches. The next two subsections are divided into authentication and identification experiments, respectively.

A. The Authentication Experiments

In this experiment, the proposed system was tested as an authentication system based on one of the most popular protocols for evaluating the performance of person authentication systems; it is the Lausanne protocol [20]. In this protocol, the users in the database are divided into two sets: clients and imposters. The performance of the verification system is tested by calculating the FAR and FRR rates as follow:

$$\boldsymbol{FA} = \frac{\boldsymbol{EI}}{\boldsymbol{I}}\times 100 \qquad (10)$$

$$\boldsymbol{FR} = \frac{\boldsymbol{EC}}{\boldsymbol{C}}\times 100 \qquad (11)$$

Where $\boldsymbol{EI}$ is the number of impostors falsely accepted as authorized users, $\boldsymbol{I}$ is the number of impostor trials, $\boldsymbol{EC}$ is the number of the falsely rejected clients, and $\boldsymbol{C}$ is the number of client trials. It is well known that reducing one of these errors can increase the other one. Hence, a tradeoff is needed between these two errors. The performance of the authentication system can be assessed after the full experiment has been performed by calculating the Equal Error Rate (EER) and Correct Authentication Rate (CAR).

Fig.5. Samples images from the SDUMLA-HMT database.

Fig.6. Samples images from the Faces96 database.

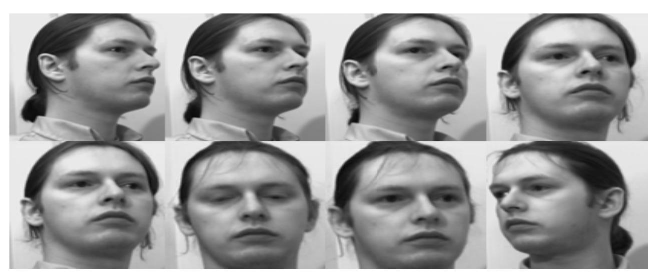

Fig.7. Eight Sample images of a person in the UMIST database.

In this paper, the proposed system was tested based on three different thresholds corresponding to FAR=0, FRR=0, and FAR=FRR. The similarity scores between the training set and other sets were calculated using the CC classifier as follows:

$$\boldsymbol{Corr(A,B)} = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right)\left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}} \qquad \textbf{(12)}$$

Where $\boldsymbol{m}$ and $\boldsymbol{n}$ are the dimensions of the sample, $\bar{\boldsymbol{A}}$ and $\bar{\boldsymbol{B}}$ are the mean values of the testing and training samples, respectively. According to the Lausanne protocol, the subjects in each database are divided into two groups of clients and imposters users. The clients' group is divided further into three sets: training, evaluation and testing sets, while the imposter's group is divided into two sets: evaluation and testing sets. The training set is used to construct clients' templates. The evaluation set is chosen to produce the access scores of clients and imposters users, which are used to establish a threshold that specifies if a subject is accepted or rejected. Based on the Lausanne protocol this threshold is assigned to meet certain performance levels on both (clients and imposters) evaluation sets. Finally, the same threshold will then be used on the testing set to simulate real authentication tests [20]. In this experiment, we found that the highest authentication rate was achieved when the FAR was equal to FRR. Table I shows the division of users for the entire database used, while the results obtained are presented in Tables II. From this table, we can see that the highest CAR was 99.32%, 96.86 % and 99.17% with EER of 0.68%, 3.14% and 0.83 %, for the SDUMLA-HMT, Faces96 and UMIST database, respectively. Hence, these results obtained demonstrate the superiority of the proposed method and the possibility of using it for the real-time face authentication system with high accuracy.

TABLE I. THE DIVISION OF PERSONS ACCORDING TO THE LAUSANNE PROTOCOL (CONFIGURATION II).

SDUMLA-HMT face database			
60 Clients		46 Imposters	
21 Images	Client's Training	20 Imposters Evaluation Dataset	26 Imposters Testing Dataset
21 Images	Client's Evaluation		
42 Images	Client's Testing		
Faces96 Database			
100 Clients		52 Imposters	
5 Images	Client's Training	20 Imposters Evaluation Dataset	32 Imposters Testing Dataset
7 Images	Client's Evaluation		
8 Images	Client's Testing		
UMSIT Database			
10 Clients		10 Imposters	
6 Images	Client's Training	4 Imposters Evaluation Dataset	6 Imposters Testing Dataset
6 Images	Client's Evaluation		
12 Images	Client's Testing		

TABLE II. THE AUTHENTICATION RESULTS OBTAINED USING (CT-FBM).

The DB. Name	Thresholds	Evaluation Set			Testing Set			
		FAR	FRR	EER	FAR	FRR	EER	CAR
SDUMLA-HMT	FAR=0	0	67.06	33.54	0	47.26	23.64	76.36
	FRR=0	66.44	0	33.23	64.57	0	32.28	67.72
	FAR=FRR	0.90	1.03	0.97	1.33	0.04	0.68	99.32
Faces96	FAR=0	0	17.57	8.78	0	16.5	8.25	91.75
	FRR=0	46.14	0	23.07	59.66	0.13	29.89	70.11
	FAR=FRR	0.31	1.43	0.86	5.16	1.13	3.14	96.86
UMIST	FAR=0	0	28.33	14.17	0	14.17	7.08	92.92
	FRR=0	9.69	0	4.84	4.79	0	2.4	97.6
	FAR=FRR	4.4	3.5	3.95	0	1.67	0.83	99.17

B. The Identification Experiments

The main aim of these experiments was evaluating and testing the reliability and efficiency of the proposed system in the identification task by comparing the query image with all the previously stored templates in the database system. Each time a different number of training and testing images were used. In this work, the proposed system was evaluated on the SDUMLA-HMT face database by dividing the person's images (84 images) into two sets, named *Database_1* and *Database_2*, containing all the odd and even numbered images, respectively. Therefore, each dataset contains 42 images for each person and 4452 images in total. Then images selected for the testing and training phases to number in the ratio 14:28, were chosen randomly for each person. The main purpose of this experiment was to show that the proposed system can give the same level of the recognition rate as shown in Table III. While, the Table IV and V show the results obtained from Faces96 and USIMT database, respectively. In this experiment the K-NN classifier was used in the classification task. The K-NN classification method is a supervised machine learning method, which was proposed by Cover and Hart [21]. The performance of the K-NN mainly depends on determining the value of the $\boldsymbol{k}$ parameter that represents the closest reference samples in the feature space. In this paper, $K=4$ for both used databases. The results obtained demonstrate that the performance of the proposed system can be slightly affected by decreasing the number of training images.

TABLE III. THE IDENTIFICATION SYSTEM RESULTS OBTAINED USING THE SDUMLA-HMT DATABASE.

The DB. Name	Recognition Rate%
Database_1	90.09
DataBase_2	90.16

TABLE IV. THE COMPARISON RECOGNITION RATE ON FACES96 DATABASE.

Training Images No.	Testing Images No.	Recognition Rate%
10	10	100
7	13	98.47
5	15	97.31
4	16	96.39
3	17	95.56
The Average RR.		97.55

TABLE V. THE COMPARISON RECOGNITION RATE ON USIMT DATABASE.

Training Images No.	Testing Images No.	Recognition Rate%
12	12	99.58
8	16	99.38
6	18	98.06
5	19	98.44
4	20	97
The Average RR.		98.492

The second aim was comparing the performance of the proposed system by taking the average recognition rate with other existing approaches. The comparative results of the proposed system and other systems using the Faces96 and UMIST databases are shown in tables (6) and (7), respectively. The recognition time was measured by implementing the proposed system on a personal computer with the Windows 8.1 operating system, a 1.80 GHz Core i5-3337U CPU and 6 GB of RAM. The system code was written to run in MATLAB R2013a. The recognition time per image was 2.24, 1.6 and 1.77 seconds, for SDUMLA-HMT, Faces96 and UMIST database, respectively. As shown in this comparative study, the results obtained demonstrated the superiority of the proposed approach on many existing approaches like, Local Binary Pattern, Scale Invariant Feature Transform and Eigenface using PCA, LDA and etc.

TABLE VI. COMPARISON OF RECOGNITION RATES OBTAINED FOR THE FACES96 DATABASE.

Recognition Algorithms	Recognition Rate %
PCA+DCT [22]	94.00
PCA + SVM [23]	94.00
Gabor Transform [24]	92.35
Local Binary Pattern [24]	82.94
LDA + SVM + RBF kernel function [25]	88.24
The Proposed Method (CT-FBM+KNN)	97.55

V. CONCLUSIONS ANA FUTURE WORK

In this work, an efficient and powerful facial feature extraction approach combining the characteristics of multi-directional transform like the Curvelet transform with fractal dimension transform is proposed. The Curvelet transform is selected as a fast and powerful technique for representing edges and curves and reducing the dimensionality of the face image, to increase the speed of the fractal dimension estimation algorithm. After that, the fractal dimension is estimated from the Curvelet's output using FBM approach. FBM is invariant to common transformations in the face image due to its self-affine property. Moreover, it has the ability to enhance the edge representation and create an illumination invariant representation of the face image without increasing the noise level. The robustness and the effectiveness of the proposed approach were proved experimentally by investigating and testing its performance using three standard face databases: SDUMLA-HMT, Face96 and UMIST. As explained above, these datasets contain face images with high diversity in facial expressions, lighting conditions, poses and etc. In addition, the results obtained demonstrated the superiority of the proposed approach when compared to the other existing approaches like, Local Binary Pattern, Eigenface using PCA, LDA and etc. The future work will focus on reducing the dimensionality of the feature vector in order to improve the recognition time using another approach for calculating the fractal dimension. In addition, this work will be extended by implementing more advanced classification algorithms based on deep learning concepts.

TABLE VIII. COMPARISON OF RECOGNITION RATES OBTAINED FOR THE UMSIT DATABASE.

Recognition Algorithms	Recognition Rate %
Regularized-LDA+Probabilistic Reasoning Model (PRM) [23]	97.5
PCA + RBF Neural Networks [26]	94.10
Scale Invariant Feature Transform (SIFT) [27]	95.95
2D-Fisher Linear Discriminant + Euclidean Distance [11]	97
Diagonal Locality Preserving Projection (DiaLPP) [12]	95.5
Pyramid Histogram of Oriented Gradients + SVM [28]	93.66
Spectral Feature Analysis (SFA) [29]	92.19
The Proposed Method (CT-FBM+KNN)	98.492

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